HYCONES: a Hybrid Connectionist Expert System

Beatriz de F. Leão , MD, PhD(1), Eliseo Berni Reátegui, MSc(2)
(1)Institute of Cardiology RS, Porto Alegre RS, Brazil
(2)Institute of Informatics, Federal University of Rio Grande do Sul, Porto Alegre, RS, Brazil

This paper describes HYCONES, a tightly-coupled Hybrid Connectionist Expert System that integrates neural networks with a symbolic approach (frames). The symbolic paradigm provides rich and flexible constructs to describe the domain knowledge, while the connectionist one provides the system with learning capabilities. The paper describes the architecture of the system, focusing on the hybrid aspects of the knowledge base and on its automatic knowledge acquisition technique from a case database. The first validation of the system is presented. At the end, a comparison with related research efforts and future developments are discussed.

INTRODUCTION

Connectionist systems attract increasing interest for their inherent learning abilities. They have been used in the development of Expert Systems (ES), in an attempt to incorporate learning capabilities and to automate the Knowledge Base (KB) construction through the use of training examples[1,2]. Connectionist systems offer an efficient solution to learning and to automatic knowledge acquisition. However, once the neural network has been trained to perform a particular task, the knowledge represented in the network sinks into a mass of connection weights, making it difficult to understand and deal with the knowledge hidden in the intermediate layers. This feature hinders the explanation of the reasoning and blocks the explanation capabilities of these systems.

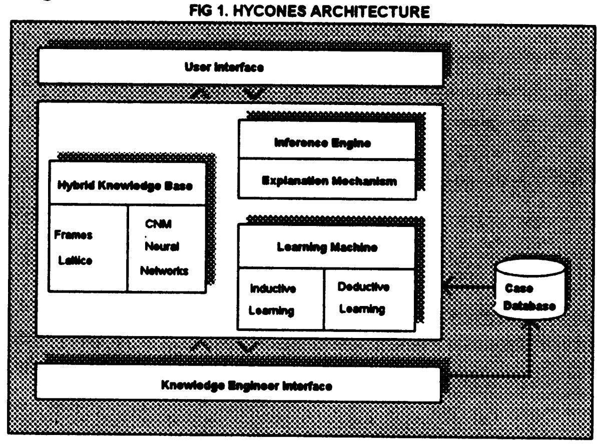
Hybrid connectionist expert systems were, therefore, proposed. In these hybrid architecture, the symbolic and the connectionist paradigms are integrated, one supporting the other. The symbolic paradigm can be used to increase the semantics of the stored knowledge, simplifying its manipulation and comprehension. The connectionist paradigm, on the other hand, offers the necessary resources for knowledge acquisition and refinement.

This paper describes HYCONES, a tightly-coupled Hybrid Connectionist Expert System that integrates the formalism of frames with a particular connectionist model [3]. HYCONES is an enhancement of an already existing hybrid system - NEXTOOL, that combined neural and semantic networks [4]. HYCONES brings enhancements to NEXTOOLS' hybrid model by creating a new knowledge representation scheme based on the use of a frames mechanism, which provides richer and more intuitive constructs for the domain description. The following section describes the **architecture of the system**, presenting the frames and the connectionist models employed, and the integration of the two paradigms, detailing the mapping of concepts between neural networks and frames. The **Implementation** section presents details about the implementation. The **Validation** section describes the first validation of the prototype. The **Conclusion** depicts the main contributions of this work and proposes further developments.

HYCONES' ARCHITECTURE

HYCONES has the following basic architecture (Fig 1):

FIG 1. HYCONES ARCHITECTURE



(1)The Hybrid Knowledge Base (HKB) that consists of a combination of a frames mechanism with neural networks; **(2) the Inference Machine (IM)** that controls the inference process through the activation of the neural networks whenever the evidences are not enough for the NN to reach a conclusion, the inference process continues with the pattern-matching mechanism in the symbolic part of the knowledge base; **(3) the Learning Machine (LM)** responsible for the inductive and deductive learning features of the system. Learning is achieved through the training and reorganization of the neural networks, and on the consequent modification of the stored frames; **(4) the Case Database (CD)** - responsible for the storage of all classification problems correctly solved. These correct classifications are used by the learning machine as the training examples for the HKB refinement.

The Frames Model

HYCONES' frames formalism provides constructs that allow the knowledge engineer to describe the domain knowledge according to the four classical abstraction concepts: generalization, classification, aggregation, and association [5]. The main objective of the symbolic component is to offer a structure to represent knowledge to solve classification problems. The application domain chosen for HYCONES was the diagnoses of the most frequent congenital heart diseases defects, as detected in the patients' database from the Institute of Cardiology RS (ICFUC). This decision was made basically because the knowledge acquisition for this domain had already been completed by a previous work [7] and it was possible to go straightforward to the implementation. To represent this type of knowledge, two different frames structures were defined: *Diagnosis* and *Finding* frames. The hierarchy of *finding-frames* uses the abstraction concepts to describe the objects of the application that influence the detection of certain diagnoses. The abstraction mechanism of aggregation was largely employed to group semantically connected classes of findings.

The *diagnosis-frames* represent the classification problems, whose structure is similar to the disease profile frames, as defined in the INTERNIST/QMR system [6]. One additional slot was defined, to describe the triggering of the diagnosis, as detailed below:

Trigger: references a *finding-frame* that, when present, singles out the *diagnosis-frame* as a potential solution to the problem;

Essential Findings: contains a list of finding-frames that must be present to assure the diagnosis identification;

Complementary Findings: contains a list of finding-frames that might be present to increase the confidence on the diagnosis;

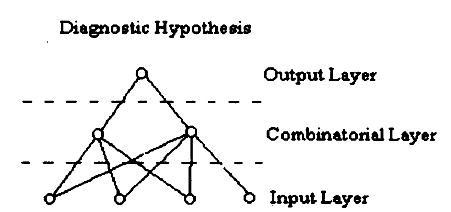
Negative Findings: contains a list of findings that can eliminate the diagnosis from the set of possible ones.

Through this Findings and Diagnosis structure, the symbolic component of the HKB is able to comprehensively represent the application domain. While the findings hierarchy describes the declarative aspects of the domain knowledge, the diagnoses hierarchy stores the possible solutions for the addressed problems.

The Connectionist Model

The same knowledge described in the diagnoses hierarchy is also represented in the neural networks. The adopted connectionist model is the Combinatorial Neural Model (CNM) [2], which was inspired on a previous paper proposing a knowledge acquisition methodology that generated knowledge graphs (KGs), described as minimally directed AND/OR acyclic graphs, representing experts' knowledge on a specific diagnostic hypothesis. [7,8]. The neural network presented in FIG. 2 depicts the basic structure of the CNM.

FIG 2. CNM Basic Structure



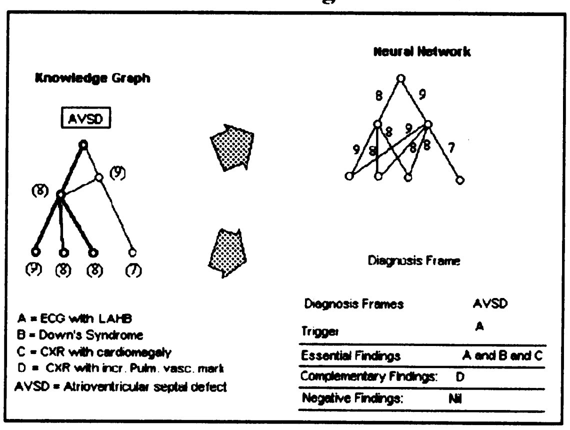
The neural network has a feed-forward topology with three or more layers. The input layer is formed by fuzzy-number cells. These fuzzy numbers, with values in the interval (0,1), represent the degree of confidence the user has on the information he observes and inserts into the neural networks. Cells in different layers are linked by connections with an associated weight that represents the influence of lower layer cells on the output of upper layer cells.

The connections of the input layer can be either excitatory or inhibitory. An excitatory connection propagates the arriving signal using its weight as an attenuating factor. An inhibitory connection perform the fuzzy negation on the arriving signal X, transforming it in 1-X. The connection then propagates the signal, multiplying the value obtained (1-X) by the connection weight. The combinatorial layers are formed by hidden fuzzy AND-cells. They associate different input cells in intermediate "chunks" of knowledge which are relevant for the diagnosis. The output layer is formed by fuzzy OR-cells, representing the degree of possibility of each hypothesis. They implement a competitive mechanism between the different pathways arising from the lower layers. Fuzzy Logic was employed in this neural network model as a way of describing quantitively the experts' knowledge represented in the KGs[8].

Integrating Neural Networks with Frames

The correspondence between the structures of the connectionist system and the frames mechanism is based on the mapping of the KGs into the neural networks and diagnosis-frames. FIG. 3 shows a KG for the diagnosis of Atrioventricular Septal Defect (AVSD) and its translation into a CNM network and the corresponding diagnosis-frame.

FIG. 3 Mapping of a KG to the neural network and to the diagnosis frame



The translation of the KG into the CNM network is direct: each of the KG's pathway leading the diagnosis conclusion is represented in a similar pathway in the neural network. This model of integration of symbolic and connectionist paradigms is classified as tightly-coupled [9]. Both connectionist and symbolic components share tasks and use resident memory structures to communicate. The tasks assigned to the connectionist component are the inference process, the inductive and deductive learning procedures, and the automatic knowledge base (KB) construction. The symbolic component is responsible for the KB consultation and for the explanation of the reasoning.

The Inference Engine

The inference process starts after the collection of findings from the environment. These findings correspond to the inputs of some of the HKB's neural networks. The networks are therefore activated, pointing to some diagnoses as potential solutions to the problem. The negative properties in the frames work as a strong inhibitory factor, that is, if they appear as an evidence, the neural networks probably will not select that frame. During the inference, several frames can be selected. Each of them will carry an evidential factor obtained from the respectively triggered neural networks. The neural network showing the highest evidential factor will be the final solution. However, this value must be higher than a minimum degree of confidence (threshold) previously defined. In case there are not enough evidences to identify the frame that solves the problem, the system requests further information from the user, based on the list of findings that appear in the *complementary-findings* slot of the selected *diagnosis-frames*. After that, the new given evidences are delivered to the connectionist inference mechanism. At the end of this cycle, the system provides a complete explanation of its reasoning.

The Learning Machine

HYCONES' learning machine is divided in 2 main components, one based on the connectionist approach, and responsible for inductive learning, and the other based on a technique similar as the recombination operator of genetic algorithms, responsible for deductive learning [10]. Inductive learning is achieved by building classification concepts (trained neural networks) through the repetitive observation of regular patterns (training examples). A pruning method is responsible for the removal from the networks of all connections whose weights are lower than a pre-set threshold. Any modification in the structure of a particular neural network implies in a subsequent change in the corresponding *diagnosis-frame*.

Deduction is here seen rather in the sense of a derivation of new concepts from something known than in the sense of a formal logic operation. Deductive learning is achieved through the use of a technique similar to the recombination operator of genetic algorithms. This method imposes further modifications in the neural network topology, creating or restoring connections between neurons. To create these new elements, the deductive learning method combines and changes the building blocks of the classifiers used in the system. By doing this, the neural networks connecting certain evidences to the corresponding hypothesis can be restructured, generating new possibilities for the solution of old problems. These new pathways are then reinforced or weakened by the punishment and reward algorithm, and finally destroyed by the pruning mechanism, keeping new and useless pathways out of the HKB.

Implementation

HYCONES was implemented in LISP environment using Goldworks III, for a PC 486. It demands at least 8 MB RAM memory. The implementation followed the object-oriented paradigm. All frames and neural networks were implemented as objects. Functions were defined as methods and incorporated in the corresponding objects. The Lisp environment was easy and friendly to work with, although sometimes slow. The neural network training from the case database took about 8 hours of CPU.

The Interface and the Case Database.

The symbolic component of the HKB consists of two different types of knowledge: knowledge about the domain and knowledge on how to solve the diagnostic problem. The first type of knowledge was represented in the hierarchy of **findings frames** and consists of a semantic model of history, physical examination, CXR and ECG findings of the congenital heart diseases (CHD) domain. This work relied on the assistance of a CHD expert and started from a list of symptoms, signs, CXR and ECG findings related to this context, already available from a previous work on knowledge acquisition on this domain[7].

Knowledge on how to diagnose, represented by the *diagnosis-frame* hierarchy, enters the system by two different modules: manual and automatic. In the manual method, the knowledge-engineer enters with the KG for each diagnosis. In the automatic mode, a case database is supplied to the system. After the case database is complete, the learning process starts and automatically creates the corresponding *diagnosis-frame* for each diagnosis. Inductive and deductive techniques are used to train the neural networks.

To create the case database for HYCONES, the three more frequent isolated congenital heart diseases diagnoses, from patients operated between 1986 to 1990, were retrieved from the surgical database of the Institute of Cardiology of RS: **ASD** - atrial septal defect, **VSD** - ventricular septal defect and **AVSD** - atrioventricular septal defect. Sixty-six patients were randomly selected from the database: 22 with **ASD**, 29 with **VSD** and 15 with **AVSD** diagnosis. The patient's history, physical examination, CXR and ECG findings were extracted from the medical files and became the evidences of the case database. For each finding extracted from the patients' file there was a corresponding *findings-frame*, previously defined in the symbolic component of the HKB. This trained case database gave origin to the first version of the HKB, named for validation purposes **B1**.

In addition to the case database, the mean KG of experts and non-experts, from the same three diagnosis above mentioned, were previously elicited by a knowledge acquisition methodology, described in [7]. The mean KG represents the consensus knowledge obtained from multiple expert's graphs on a specific problem domain [8]. The second version of the HKB, named **B2** for validation purposes, contains the mean KG of the experts, while the third version of HKB, named **B3,** carries the mean KG of the non-experts. After that, the hybrid knowledge bases **B2** and **B3** were submitted to the same learning procedure as the case database, giving origin to two other versions of the HKB, named **B2T** and **B3T,** respectively.

VALIDATION

To validate HYCONES performance, 33 cases were randomly selected, 13 with **ASD** diagnosis, 10 with **VSD** diagnosis and 10 with **AVSD,** covering the same period, from the same database that originated the case database. The cases already included in the case database were excluded from this selection. These 33 cases had their patients' histories, physical examinations, CXRs and ECGs findings as evidences offered to HYCONES in its consultation mode, addressing the five different knowledge-bases: **B1** - the system trained from the case database, **B2** - experts' mean KGs, **B2T** trained experts' mean KGs, **B3** non-experts' mean KGs, and **B3T** trained non-experts' mean KGs . The results are in TABLE I below.

TABLE I
HYCONES VALIDATION

Diagn	B1	B2	B2T	B3	B3T
Correct	31	14	26	0	28
Wrong	0	3	0	0	0
Not enough evidence	2	16	7	33	5
Total	33	33	33	33	33

The validation showed that the HKB trained by the case database **(B1)** presented the best results: 31 out of 33 diagnoses were correctly diagnosed. The 2 diagnoses on which **B1** had not enough evidence to conclude were, in fact, not isolated lesions. One had an ASD and a Pulmonary stenosis, while the other was a VSD with a severe pulmonary hypertension. The case database was not trained to recognize either of these two diagnoses. There was no statistical significance singling out the performance of **B2T**, **B3T** or **B1**. It must be stressed that what is being evaluated is not the expert's knowledge itself, but rather the mean knowledge graph extracted by a specific methodology of knowledge acquisition.

CONCLUSION

There are several contributions to single out in this project: (1) the definition of a mechanism to integrate the frames paradigm with neural networks. This integration adds the adaptive features of neural networks to the symbolic knowledge representation of the domain, clarifying what is hidden in the intermediate layers of the connectionist component; (2) the specification of a method to acquire knowledge to solve a diagnostic problem, based on the training from a case database. Furthermore, based on this training the system is able to automatically construct the corresponding symbolic representation of what it has learned; (3)the manual knowledge acquisition phase, considered as the bottleneck in the construction of expert systems, is simplified by the direct translation of knowledge graphs into the neural networks and, consequently, into the HKB; (4) the definition of a strategy to simulate deductive learning, able to reorganize the knowledge already stored in the knowledge-base, creating new concepts through the recombination of the evidences, improving the system's performance. The formation of knowledge germs when grouping the knowledge graphs elicited from various experts has already been described [7,8]. These knowledge germs represent the most important heuristic rules used by experts upon diagnosing cases they are dealing with. The same behavior was detected in the CNM neural networks, that is, the formation of the strong pathways they commonly use to reach a diagnosis. Even though the first evaluation of HYCONES was very promising there are still many improvements to be accomplished. Functions to better define the semantic connections in the domain are still lacking, mainly to cope with the identification of similarities in medical findings.

REFERENCES

[1] Gallant S. I. Connectionist Expert Systems. Communications of the ACM, New York, **31**, 152-169, 1988.

[2] Machado R. J. & Rocha A. F. The Combinatorial Neural Network: a Connectionist Model for Knowledge-Based Systems. Proceedings of the Third International Conference IPMU - Information Processing and Management of Uncertainty in Knowledge-Based Systems, Paris, 9-11, 1990.

[3] Fikes R. & Kehler T. The Role of Frame-based Reasoning. Communications of the ACM, New York, **28**, 904-920, 1985.

[4] Machado R. J. & Rocha A. F. A Hybrid Architecture for Fuzzy Connectionist Expert Systems. Intelligent Hybrid Systems, CRC Press Inc, 1992.

[5] Hull R. & King R. Semantic Database Modeling: Survey, Applications, and Research Issues. ACM Computing Surveys, **19**, 201-260, 1987.

[6] Miller R. A. et al. Internist-I, An Experimental Computer-Based Diagnostic Consultant for General Internal Medicine. In: Reggia J. A. & Tuhrim S. (eds.). Computer Assisted Medical Decision Making, vol. 2. Nova Yorque:Springer Verlag,1985.

[7] Leão B. F. & Rocha A.F. Proposed Methodology for Knowledge Acquisition: A Study on Congenital Heart Disease Diagnosis. Methods of Information in Medicine, **29**, 30-40, 1990.

[8] Machado R. J., Rocha A.F. & Leão B.F. Calculating the Mean Knowledge representation from multiple experts. In: Fedrezzi M. & Kacprzkyk J. (eds.). Multiperson Decision Making Models Using Fuzzy Sets and Possibility Theory, The Netherlands, Kluwer Academic Publishers, 1990.

[9] Medsker L. R. & Bailey D. L. Models and Guidelines for Integrating Expert Sistems and Neural Networks. In:: KandelL A. & Langholz G. Hybrid Architectures for Intelligent Systems, CRC Press, 1992.

[10] Carbonell J. G. . Introduction: Paradigms for Machine Learning. Artificial Intelligence, 1-9, 1989.